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A two-phased SEM-neural network approach for consumer preference analysis

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ABSTRACT

A fundamental task in the design of consumer products is consumer preference analysis. The primary focus of this task is establishing a mapping relationship between product parameters/attributes and consumer preferences. The key to connect the consumer space and the design space are user perceptions of the product. Among the many existing methods, the Structural Equation Model (SEM) is one of the most used methods because it explains the causal relationship between the input and the output variables explicitly. However, the relationship obtained from the conventional SEM is linear, which is usually not the case in practice. Fortunately, the Artificial Neural Network (ANN) provides a new perspective for building nonlinear models because of its nonlinear nature. Therefore, a two-phased SEM-NN approach for consumer preference analysis is introduced for identifying and mapping how product attributes affecting the fulfillment of user perceptions and ultimately their preferences. In this model, the consumer preference analysis is conducted in two phases: influence path construction, and path coefficient revision. The proposed method can reserve the original SEM topology that reflects the causal relationship between variables while using the training algorithm of ANN to obtain more accurate path coefficients. This model could help the designers to identify and map how product attributes affecting the consumer preferences, and to better understand the factors that affect user perceptions and the inner relationships between them. To demonstrate effectiveness of the model, a case study of smartphone is presented. It is shown that the SEM-NN model can make full use of the causal analysis of SEM and the nonlinear nature of ANN and ultimately provides more reliable results of consumer preference analysis.

1. Introduction

Consumer preference analysis is a fundamental task in the design process of consumer products. The primary focus of this task is establishing a mapping relationship between consumer preferences and product parameters/attributes. The key to connect the consumer space and the design space are user perceptions of the product. User perception refers to the unique experience that users have when using a product. Users usually use words like comfort, satisfactory, attractive, slow, unreliable to describe the experience. For the fact that the preference model reveals the relationship between the consumer preferences and product attributes, it is widely used in product development, market segmentation, brand competition analysis, pricing strategy and other fields.

Traditionally, methods like choice analysis (CA) are used to map the consumer information onto a single construct—utility. The consumer preferences are determined by the utility provided to the consumer by a product or service. The utility refers to the ability of a product or service to satisfy the user's needs and desires, which reflects the satisfaction that consumer felt when using a product or enjoying a service. The Discrete Choice Models (DCM) is a common method for consumer preference analysis [1–4]. On the basis of DOE (Design of Experiment) [5], the DCM can measure user's purchase behavior by simulating the product or service in the market competition environment. The user's choice between different products or services can be obtained through the DCM. In DCM, the dependent variables are multiple products that can be selected by users and the independent variables are the different product attributes, so nonlinear multivariate regression is a main analysis method for DCM. The logistic regression was used to analyze the relationship between dimensions of international express service and user preference, so that to provide new ideas for the design of international express service [6]. The multiple linear regression and support

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vector regression was used to analyze the relationship between product design features and user preference, which can help designers optimize product design and improve practical values [7]. Besides, other methods to analyze the user preference in the field of economics include correlation analysis [8], clustering analysis [9], neural network [10], network analysis approach [11,12] and so on. For all above methods that originated in the market domain, they allow designers to understand the important design parameters/attributes that affecting the fulfillment of consumer perceptions and ultimately their preferences [13]. In these methods, however, the user information is usually mapped to a set of utilities. The designers can only get what the user's preference is, but do not know how the specific preference is generated or which attribute has more influence on the user's preference. That means these methods cannot reveal the specific emotional changes of users in the mapping procedure.

Another dimension to study the consumer preference comes from the behavioral research in the field of psychology. Theory of Reasoned Action (TRA) [14] expatiates people are rational individuals and they would consider the effects and results before taking any action. So TRA can be used to analyze the determinants of conscious intention and behavior. The premise of TRA is that individuals have rational control abilities, but, the actual behavior cannot be determined only by the subjective factors of the individual, but also influenced and restricted by the objective factors.

In the study of technology adoption/acceptance model, Davis [15] proposed the Technology Acceptance Model (TAM), trying to explain the impact of external factors, user beliefs and user attitudes on the usage intention and actual usage behavior of the information system. TAM has been widely used in interpreting and predicting user information technology acceptance behavior, and some improved models of TAM have been developed to analyze user's behavior in other fields, such as TAM2 (Technology Acceptance Model2) [16] and UTAUT (Unified Theory of Acceptance and Use of Technology) [17] and TAM3 (Technology Acceptance Model3) [18]. In above methods, user's ideas, perceptions, and attitudes are mapped into a network to predict downstream user preference. Through this network the reasons behind users' specific perception or preference can be traced, which can provide designers with more abundant information about user preference.

In order to verify the relationship between the factors of network, the Structural Equation Model (SEM) [19] is a commonly used technique for parameter estimation and hypothesis testing. SEM is a general statistical technique for the estimation of a system of simultaneous linear equations that may include both observed and latent variables [20]. That is, SEM techniques have made it possible for researchers to examine theory and measures simultaneously [21]. SEM are widely used in examining a variety of structures, including causal models, measurement models, growth models, and combinations of these. For instance, in Ref. [22], SEM was used to explore how the performance of the project participants affects the contractor's satisfaction. They established a model to analyze the customer's goal clarity, construction risk management, and mutual respect and trust on the impact of the customers' satisfaction. Ghosh et al [13] mapped the user's various psychological constructs and their relationships into a network, and then used the SEM to verify the proposed model. Despite that the SEM method has been widely applied in many fields, the assumption that the relationships between variables are linear limits the depth of its application. Previous research have proved that there is a nonlinear relationship between product quality and customer satisfaction [2324]. In some cases, it may oversimplify the complexities involved in the causal paths.

With the increasing complexity of the model, researchers have called for new SEM techniques to solve this issue. Some scholars try to improve the conventional SEM to express the nonlinear relationship between variables by introducing the quadratic and interaction term of the variables into the model [25,26]. However, one substantial drawback is that such approaches assume that the latent linear predictor variables are multivariate normally distributed. When this assumption is violated, the parameter estimates in the nonlinear SEM can be biased [27]. Fortunately, the Artificial Neural Network (ANN) [28] provides the ability of self-learning and the nonlinear characteristic to fit the nonlinear relationship between multiple variables. In general, the topology of an ANN is a fully connected network that determined by the experience of engineers, which makes it difficult to explain the causal relationship between input and output variables. In addition, it is often difficult to construct a neural network model when learning from data. Employing the results from SEM provides a way to develop a neural network model with a good prediction performance [29]. There are different types of multiple-analytic approaches that combined SEM and ANN. For instance, SEM can be used to analyze part of the question responses, while the rest of the responses can be predicted by ANN [30]. Hackle and Westlund [31] contended that the ANN-based SEM technique can be superior to conventional SEM because it can measure nonlinear relations by using different activity functions and layers of hidden nodes. Scott and Walczak [32] applied a multi-analytic approach for assessing computer self-efficacy (CSE) and technology acceptance, in which the SEM were used to test the hypotheses and the reliability of the measures, while NN analysis verifies the antecedents as predictors of CSE, estimates CSE scores, and assigns individuals to groups based on their CSE scores. Using the output result of ANN as SEM's input is also a common approach [32,33]. Although the SEM-neural networks have been applied to some problems, including assessing technology acceptance [29,33–35] and customer relationship management (CRM) adoption [36], they have not been previously used for consumer preference analysis.

In this paper, a two-phased SEM-neural network approach is proposed, in which the topological structure is obtained from the conventional SEM and the path coefficients are obtained from the BP algorithm-based training process. Firstly, the causal relationship between the product attributes and user preference are obtained from the topological structure of the conventional SEM. Then, the self-leaning process based on the BP algorithm is conducted to train the ANN based on SEM results to get the revised path coefficients. Finally, the proposed model is used to fit the user's preference on the smartphone in a case study.

2. Methodology

The proposed method includes two phases.

In Phase I, the SEM is used as a parameter estimation and hypothesis testing technique to obtain the influence path between the user's multi-dimensional perceived performances and user's preference. Firstly, the assumptions of the user preference model are proposed, including: 1) the relationships between the dimensions of the perceived performances and the user preferences; 2) the indicators for each dimension of the perceived performances. Then, a questionnaire is designed based on the perceived performances indicators. Taking smartphone users as an example, the questionnaires are applied to quantify the user's perceived performances for the smartphone, including the perceived responsiveness, the perceived endurance, the perceived functionality and so on. Finally, the questionnaire data are used to analyze and optimize the SEM model. The optimal relationships between the dimensions of the perceived performances and the user preference then can be obtained.

In Phase II, the structure of the SEM model, which represents the influence paths between user's multi-dimensional perceived performances and user preferences, is used as the design basis of the neural network topology. Then, the Back Propagation (BP) algorithm originally applied in ANN is used to train the coefficients of those influence paths. Finally, the Root Mean Square Error (RMSE) and the coefficient of determination (R^2) are used to evaluate the performance of the model.

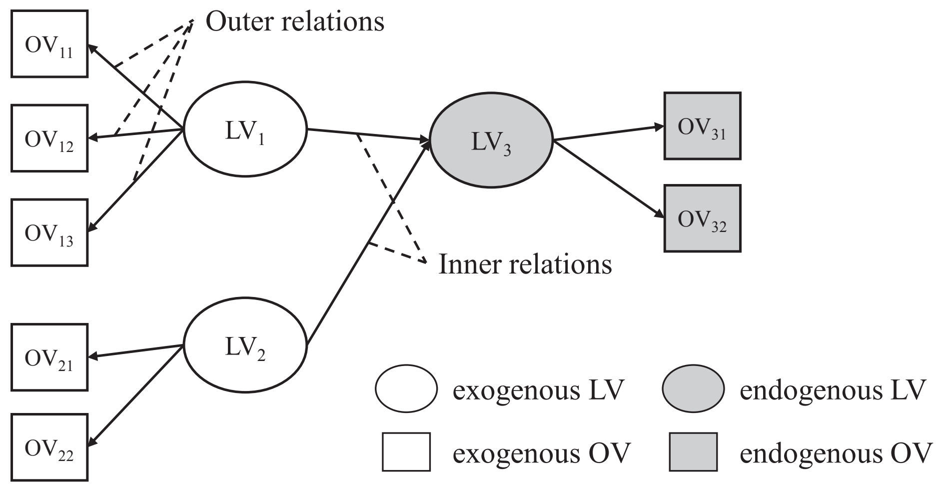

Fig. 1. The structure of a simple SEM model.

2.1. Phase I: Influence path construction and validation

SEM is a statistical framework for the analysis of latent variable models. SEM models are commonly specified via a path diagram or a system of structural equations. The path diagram is a valuable tool in helping investigators better understand the research questions and the data, and forcing them to think critically about every variable relevant to the problem [20]. There are two types of variables in SEM model, observable variables (OV) and latent variables (LV). Observable variables are the variables can be measured directly. Both variables could be divided into exogenous (variables whose causes are not included in the model) or endogenous (variables whose causes are posited in the model). One of the key features of SEM is that multiple observed variables can be combined into *latent variables*, which cannot be directly observed, but can be inferred from the covariances shared among the corresponding OVs [20]. For example, multiple measures of the responsiveness of a smartphone can be combined into a LV as “perceived performance”.

Fig. 1 shows the structure of a simple SEM model, where OVs are represented as rectangles and LVs are represented as circles. A SEM model may include two types of LVs – exogenous LVs and endogenous LVs. It consists of two kinds of linear relationships – inner relations and outer relations. Inner relations specify relationships among LVs and outer relations describe relationships among the LVs and the corresponding OVs. SEM techniques provide researchers with the flexibility to model relations among multiple endogenous and exogenous latent LVs, and simultaneously to construct the relations between LVs and OVs.

Generally, a SEM model consists of two components: a measurement model and a structural model. The structural model is used to specify and test the relationships among variables. The measurement model describes the relationship between LVs and OVs. The confirmatory factor analysis (CFA) [37] can be used to verify the relationship, thus reducing the workload of the modeling process of the structure model. In the following sections, the construction of these two models will be introduced respectively.

2.1.1. The measurement model

Latent variables are usually not observed directly and need to be expressed through multiple corresponding observed variables. The observed variables are determined by the following steps:

Step 1: Determine the exogenous OVs.

Select all the performance parameters that affect the user perception. Then collect the operation data of the parameters and the user's perception feedback. By the Gamma correlation analysis, the performance parameters with significant correlation to user perception were determined as the exogenous variables. For endogenous OVs, the indicators are quantified by benchmarks or comparison.

Step 2: Measurement model verification and modification.

The Confirmatory Factor Analysis (CFA) [37] is used to verify the relationship. Based on the result of the CFA analysis, including significance test and the value of factor loading, some OVs that are not significantly related to user perceptions can be deleted to reduce the workload of structure model. The proposed models are tested and modified iteratively until converged to an optimal model which can be used as the basis for constructing the topological structure.

2.1.2. The structural model

The hypothesis of the structural model is mainly based on the existing theoretical research and the practical experience of engineers and designers. The hypothesis relationship between latent variables forms the theoretical framework of statistical test. This paper presents the assumptions of the structural model by the following steps:

Step 1: Select the SEM variables of structural model based on the

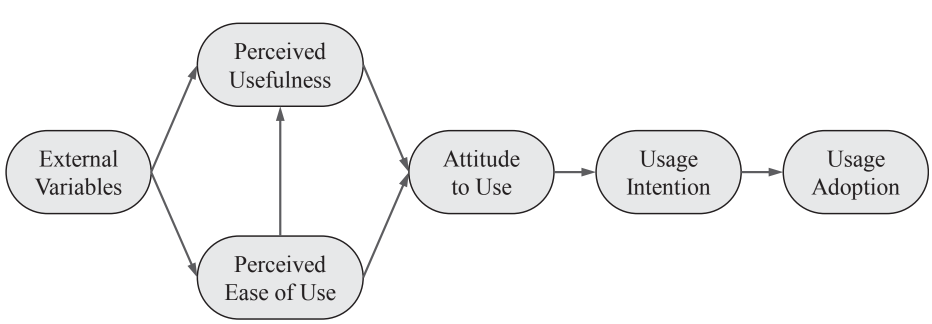

Fig. 2. The framework of TAM.

TAM

In the TAM, the user's ideas, perceptions and attitudes are mapped into a network to predict downstream user preference, as shown in Fig. 2. The formative measures are the observed variables that considered being the cause of the latent variable; while the reflective measures are the indicators of a construct that are considered to be caused by that construct. Through this network the causes behind user's specific perception or preference can be traced, thus provides the designers with more effective information about user preferences. When initiating the hypothetical model, we should build as many paths as possible based on theoretical knowledge and practical experience, so that the model can reflect the latent relationship between variables more comprehensively.

Step 2: Modify the influence path between perceived performance and user preference one by one.

Structural equation model consists of measuring model and structure model, each modification of the model will generate different estimates for the parameters of both the measurement model and the structure model. Hence, whether the variables in the measurement model are added or ignored, or the paths in the structural model are added or deleted, they need to be carried out one by one, and then the parameters of the model need to be re-estimated until the model is well fitted.

2.2. Phase II:Path coefficient revision

2.2.1. Model training with the BP algorithm

The structure of the SEM model can be regarded as an ANN model with partially connected nodes. Fig. 3 depicts an example of a SEM-based ANN structure with two hidden layers. The number of the input nodes is determined by the number of formative measures. The number of formative measures is assumed to be I, noted as $x_i (i = 1, 2, 3, ...I)$. The number of hidden layers and the number of the neurons in the hidden layer are determined by the number of exogenous latent variables and endogenous latent variables. It is assumed that there are W exogenous latent variables and N endogenous latent variables respectively, with $\xi_w (w = 1, 2, 3, \cdots, W)$ and $\eta_n (n = 1, 2, 3, \cdots, N)$. The number of the output neurons is determined by the number of the reflective measures, assuming there are O reflective measures noted as $y_o (o = 1, 2, 3, ...O)$. The connections between layers are determined by the relationship between the measures and the latent variables. The connection weights of the neural network correspond to the factor loadings (between the measures and the variables) and the path coefficients (between the exogenous variables and the endogenous variables) in the SEM. The connection weights between the input layer neurons and the hidden layer neurons is $W \times I$ dimensional vector, noted as W^I. The connection weights between the hidden layer neurons is $N \times (W + N)$ dimensional vector, noted as W^H. The connection weights between the hidden layer neurons and output layer neurons is $O \times N$ dimensional vector, noted as W^o. Every neuron in neural network contains a nonlinear activation function. In this paper, the activation functions of all neurons are Sigmoid functions.

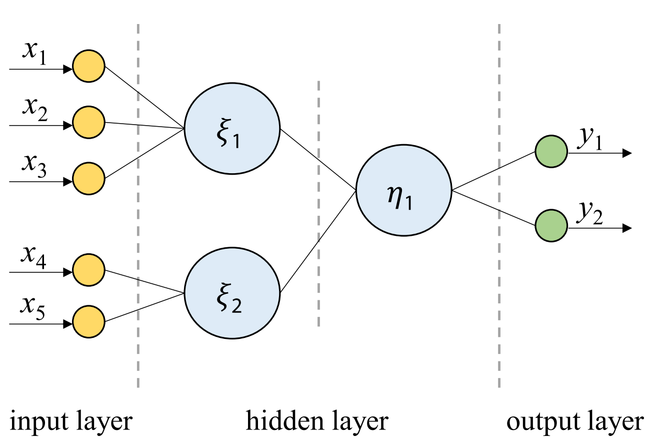

Fig. 3. An artificial neural network topology based on SEM.

Suppose that the sample is $X = [X_1, X_2, X_3, \cdots X_P]$, the inputs for each sample are the values of formative measures, $X_p = [x_{p1}, x_{p2}, x_{p3}, \cdots, x_{pI}] (p = 1, 2, 3, \cdots, P)$, the expected outputs are the actual values of reflective measures, $D_p = [d_{p1}, d_{p2}, d_{p3}, \cdots, d_{pO}]$.

The training procedures include two steps:

Step 1: the input and expected output vectors are standardized by Box-Cox Normalization method [38], and the weights W^I, W^H and W^O are initialized according to the result of SEM analysis, then the BP algorithm [39] is used to train the connection weights between network nodes in the model.

Step 2: According to the sample data, the BP algorithm is implemented in two stages to obtain the connection weights between the network nodes.

The BP algorithm is implemented as following two stages:

1) The forward propagation

The input data enters the entire network from the input layer, when the network nodes are only used for input without any calculation. Computing operations such as weighted summation, nonlinear activation, etc. are performed in the hidden layer. The output data are then sent to the next layer for the same calculation until the final output of the model is $Y_p = [y_{p1}, y_{p2}, y_{p3}, \cdots, y_{pO}]$. The details of the forward propagation are as follows:

For each training sample, the input is the value of the exogenous measurement variable, noted as $X_p = [x_{p1}, x_{p2}, x_{p3}, \cdots, x_{pI}]$ $(p = 1, 2, 3, \cdots, P)$. To eliminate the deviation caused by the dimensional difference between different variables, the z-score method is used to normalize the input sample data as follows:

$$x_{pi}^* = \frac{x_{pi} - \mu_{x_i}}{\sigma_{x_i}} \tag{1}$$

where $\mu_{x_i}$is the sample mean of the exogenous measurement variable x_i, and σ_{x_i} is the sample standard deviation of the exogenous measurement variable x_i.

The output of the neural network model corresponding to each training sample is the predicted value of the endogenous measurement variable, $Y_p = [y_{p1}, y_{p2}, y_{p3}, \cdots, y_{pO}]$; The expected output is the sample value of the endogenous measurement variable, $D_p = [d_{p1}, d_{p2}, d_{p3}, \cdots, d_{pO}]$; Since the activation function of output neurons is set as Sigmoid function, the sample values of endogenous measurement variables are normalized by max–min method:

$$d_{po}^* = \frac{d_{po} - \min\limits_{p=1,2,3\cdots,P} d_{po}}{\max\limits_{p=1,2,3\cdots,P} d_{po} - \min\limits_{p=1,2,3\cdots,P} d_{po}}, \ o = 1, 2, 3, \cdots, O \tag{2}$$

According to the topology of the neural network model, input layer nodes and the weights between the hidden layer nodes is vector W^I, according to the previous definition, its dimension is $W \times I$; the weight vector between the hidden layer nodes is W^H, in the same way, the dimension is $N \times (W + N)$; the weight vector of the hidden layer to output layer is W^O, and the corresponding dimension is $O \times N$.

Firstly, initialize the W^I, W^H and W^O. The initiation for conventional ANN usually employs the random method, but the topological structure of the SEM is constructed from the SEM analysis, so the standardized factor loading for the measurement model and the path coefficient values for the structural equation model can be used as the initial weights. The weight vector W^I is used to weight the input value of the external measurement variable, and then it is input to the network node corresponding to the external latent variable. After the sum and the Sigmoid activation function processing, the output of the network nodes corresponding to the external latent variables are obtained as follows:

$$\xi_{PW} = sigmoid(W^I \bullet X_P + b^I) \tag{3}$$

Then, the output of the network nodes related to the exogenous latent variables is input to the network nodes related to the endogenous variables. The weight vector W^H is used to weight the input value, and after the process of the nonlinear Sigmoid activation function again, the output of the network nodes related to the endogenous latent variables can be obtained as follows:

$$\eta_{PN} = sigmoid(W^H \bullet \xi_{PW} + b^H) \tag{4}$$

If the next network node is still the network node corresponding to the endogenous latent variable, the output of the previous node will be taken as the input of the network node related to the next endogenous latent variable. Then the weight vector W^H is used to weight the input value and get the output after the process of the Sigmoid activation function.

Finally, the output of the network nodes related to the endogenous latent variables are input to the network node related to the endogenous measurement variables, i.e. the output layer of the model, The weight vector W^O is used to weight the input value, and after the process of the nonlinear Sigmoid activation function again, the final output are obtained as follows:

$$Y_{PO} = sigmoid(W^O \bullet \eta_{PN} + b^O) \tag{5}$$

2) The back propagation

The total output error is calculated according to the model output and the desired output. The output error is the spread forward layer by layer to calculate the error of each hidden layer neuron. The Delta learning rule [40] is used to constantly adjust the connection weights of the network so as to minimize the total model error. The specific process for the back propagation is as follows:

Set up the training times of the SEM model as t, the connection weights, bias, and output of the SEM model are all functions of t. The connection weights and bias of the model can be uniformly noted as $w(t) = \langle W(t), b(t) \rangle$.

According to the output $Y_p = [y_{p1}, y_{p2}, y_{p3}, \cdots, y_{pO}]$ and expected output $D_p = [d_{p1}, d_{p2}, d_{p3}, \cdots, d_{pO}]$, the mean square error (MSE) can be calculated as the loss function as follows:

$$E[w(t)] = \frac{1}{2O} \sum_{p=1}^{P} \sum_{o=1}^{O} (y_{po} - d_{po})^2 \tag{6}$$

The gradient of $w(t)$ then can be obtained by taking the partial derivative of the corresponding parameter with respect to the output error as follows:

$$f^T(t) = \nabla E[w(t)]|_{w=w(t)} \tag{7}$$

According to the vector $f^T(t)$, the size of (t) for the next iteration can be determined as follows:

$$\Delta w(t) = -c \bullet f(t) \tag{8}$$

$$w(t+1) = w(t) + \Delta w(t) \tag{9}$$

where c is the learning rate and can be set to be a small positive number, which means that the correction of network connection weight is taken as a small value along the direction of the negative gradient of the error surface.

2.2.2. Model evaluation

The commonly used criteria for evaluating structural equation models with latent variables can be found in Bagozzi and Yi's work [41]. In this paper, various standards for evaluating different part of SEM are defined, and empirical examples are provided. The evaluation criteria have become the most commonly used indexes for SEM evaluation.

In addition, to quantitatively illustrate the effectiveness of the proposed SEM-NN approach, 80% of the original sample is selected randomly as training data and 20% of the sample as test data. Two criteria are selected to evaluate the performance of the model: the root mean square error (*RMSE*), that measures the prediction accuracy of the model, and the determination coefficient R^2, that measures the fitting goodness of the model. The prediction accuracy is higher as the *RMSE* closer to 0, and the fitting goodness is better as the R^2 is closer to 1. The two criteria are calculated as follows:

$$RMSE = \sqrt{\frac{1}{P} \sum_{p=1}^{P} (y_{po} - d_{po})^2}, \; o = 1, 2, 3, \cdots, O \tag{10}$$

$$R^2 = 1 - \frac{\sum_{p=1}^{P} (d_{po} - y_{po})^2}{\sum_{p=1}^{P} (d_{po} - \bar{d}_o)^2}, \; o = 1, 2, 3, \cdots, O \tag{11}$$

where $\bar{d}_o$ is the sample mean of the reflective measures, that can be calculated by:

$$\bar{d}_o = \frac{\sum_{p=1}^{P} d_{po}}{P}, \; o = 1, 2, 3, \cdots, O \tag{12}$$

3. Case study

Smartphone is one of the most representative smart products. And the smartphone manufacturers have paid much attention to the perceived performances of smartphone users. A case study of smartphone is presented in this section to demonstrate the effectiveness of the proposed methodology.

3.1. Experimental protocol and data acquisition

In this work, both the formative and the reflective measurement items for each user perception are based on the corresponding questions in the questionnaire. The items involved in the questionnaire were designed based on the literature and earlier studies [42–46] and by consulting an expert who works for a Chinese smartphone manufacturer (see Table 1). Then the questions were customized and adjusted to adapt to the circumstances of this research. The full questionnaire (in Chinese) can be found on the Internet (https://www.wjx.cn/jq/15616784.aspx). The dimensions of smartphone perceived performances including the perceptions on the *responsiveness*, the *battery endurance*, the *functionality*, and the *design and brand appeal*. The questionnaire for each dimension of perceived performances is evaluated by 7-point Likert scale, 1 to 7 represent "strongly disagree" to "strongly agree".

To get more users to participate, the study conducted a questionnaire survey both online and offline. A total of 182 questionnaires were collected and 168 questionnaires were valid in this case study. The demographic statistics of 168 survey subjects are shown in Fig. 4, including phone OS, gender, age, and education.

The calculation for the topological construction of SEM was completed using SPSS-Amos21 software, and the training of the ANN was written by the Python3.6.

3.2. Phase I: Influence path construction

The KMO and Bartlett's Sphericity test are used to test whether the results of questionnaires are suitable for SEM analysis [47]. The KMO value is 0.730 greater than 0.7, and The Chi-square value is 1534.853 with 231 freedoms, which is significant for the Bartlett's Sphericity test. Therefore, the data are suitable for factor analysis. The structural equation model was used for further analysis of the survey data.

3.2.1. Measurement Model—Confirmatory factor analysis

The CFA is used to test the significance of formative measures and reflective measures. And the insignificant measures need to be removed

Table 1
Questionnaire items and references.

Constructs	Items	References
Design and Brand Appeal	I like the appearance design of this phone I am satisfied with the size and weight Brand awareness is important to me I think my phone brand is a status symbol	Hou et al. [42] Yeh et al. [43] & Expert experience
Perceived Responsiveness	Application loading speed is fast Application switching speed is fast Application installation is fast Performance reliability is good	Expert experience
Perceived Battery Endurance	Battery life is solid I need a portable charger I have low-battery anxiety Charging speed is fast	Ferreira et al. [44] & Expert experience
Perceived Functionality	I am satisfied with the functionality completeness I am satisfied with the functionality richness Functionality needs improvement	Expert experience
Perceived performance	Using this phone is delightful This phone is easy to use Using this phone is frustrating Using this phone is annoying	Liu and Yu [45] & Expert experience
User Preference	This is a good phone for everybody I am satisfied with this phone I will recommend this phone to my friends	Lee [46] & Expert experience

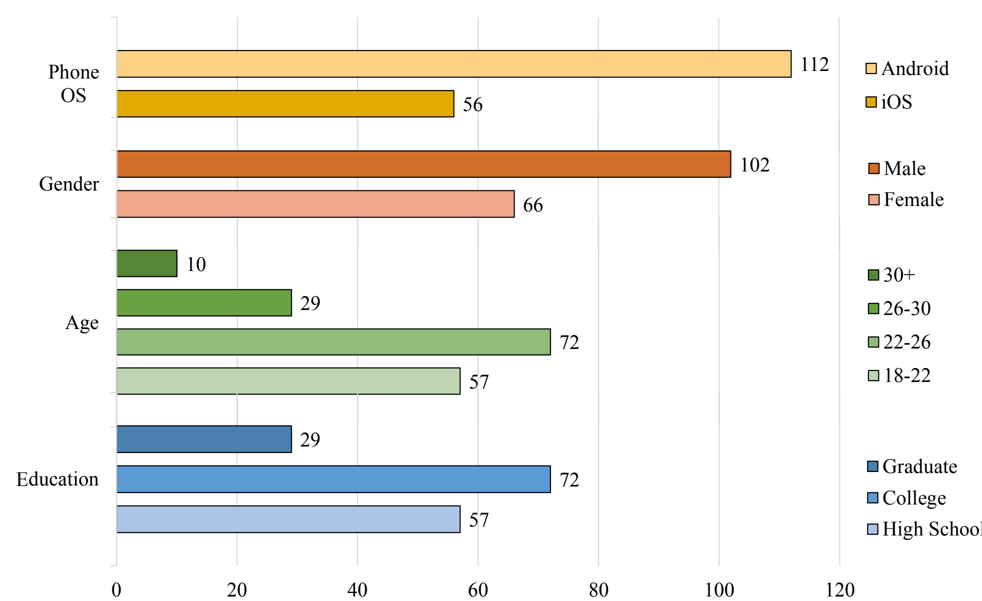

Fig. 4. The demographic statistics of the survey subjects.

until all measures are statistically significant, and the factor loading is generally acceptable. In this case study, the measurement data are collected using a questionnaire, which help users "reflect" on their product usage and other psychological constructs such as their perceived functionality. The items of all six constructs are reflective measurements. In this model, the constructs are posited as the common cause of the measurements and causal action flows from the construct to the measurements.

Table 2
Reliability and validity tests.

Physical construct	Factor loadings	Cronbach'sα	CR	AVE
Design and Brand Appeal	0.618–0.767	0.695	0.736	0.653
Perceived Responsiveness	0.604–0.757	0.715	0.721	0.603
Perceived Battery Endurance	0.534–0.771	0.658	0.795	0.701
Perceived Functionality	0.540–0.705	0.632	0.671	0.558
Perceived performance	0.813–0.864	0.821	0.839	0.724
User Preference	0.820–0.859	0.846	0.876	0.773

The results of measurement model are shown in Table 2 and Table 3. All standard factor loadings are more than 0.5 and significant, indicating that those measures are acceptable for specific dimensions of perceived performance. Cronbach's alpha is applied to measure the reliability. The ideal value of Cronbach's alpha should be greater than 0.70, and 0.60 is the lower acceptable limit. The Composite Reliability (CR) is used to measure the consistency of the formative measures and the reflective measures. The Average Variance Extracted (AVE) is used to measure the interpretability of the formative measures and the reflective measures. The results in Table 2 show that the values of the Cronbach's alpha of all the factors were greater than 0.6, the values of CR are greater than 0.6, and the values of AVE are greater than 0.5. The values of CR are higher than those of AVE, which confirmed the convergent validity. Then, the discriminant validity was verified. As shown in Table 3, the AVE value of each structure is greater than the squared

Table 3
Discriminant validity of measurement items.

	CR	AVE	DBA	PR	PE	PF	PP	UP
Design and Brand Appeal (DBA)	0.933	0.903	0.831					
Perceived Responsiveness (PR)	0.944	0.922	0.609	0.867				
Perceived Endurance (PE)	0.948	0.913	0.503	0.762	0.872			
Perceived Functionality (PF)	0.954	0.928	0.477	0.329	0.646	0.898		
Perceived Performance (PP)	0.941	0.833	0.488	0.543	0.491	0.541	0.830	
User Preference (UP)	0.958	0.927	0.535	0.436	0.506	0.611	0.753	0.838

Table 4
The path coefficients and fit indices of SEM model.

Influence Path						Coefficient	C.R.	p
Perceived Performance		←	Perceived Responsiveness			0.514	5.281	< 0.001
Perceived Performance		←	Perceived Endurance			0.390	3.805	< 0.001
Perceived Performance		←	Perceived Functionality			0.224	2.557	0.011
User Preference		←	Perceived Performance			0.652	8.105	< 0.001
User Preference		←	Design and Brand Appeal			0.503	5.631	< 0.001
Fit Indices	χ^2	χ^2/df	PGFI	PNFI	IFI	CFI	GFI	RMSEA
Value	200.561	1.090	0.718	0.750	0.986	0.986	0.901	0.023

correlation coefficient between the given and other structures; therefore, discriminant validity was supported as well.

3.2.2. Structural model

After the measurement model is constructed, the structural model is applied to analyze the relationship between the perceived performances and the user preference. The standardized path coefficients between the dimensions of perceived performances and user preference, and the fit indices of the model are shown in Table 4. The complete fitting results of user perception model based on SEM is shown in Fig. 5. In the figure, i_1 to i_{22} are the specific measurement indicators perceived by users, corresponding to 22 questions in the questionnaire. The indicator i_4 is excluded from the model because it did not pass the measurement model analysis. e_1 to e_{22} are the error terms of measurement model, e_{01} and e_{02} are the residual terms of perceived performance and user preference.

Firstly, from the above results of parameter estimation, the relationship between the user psychological constructs (perceived performances and user preference) is significant. Then, the fit indexes of the model are tested. The Chi-square value is 200.56 with 184 freedoms, $\chi^2/df = 1.090 < 2$, that is close to 1, indicating that the covariance matrix of sample is similar to the estimated covariance matrix. The parsimonious fit measures $PGFI = 0.718$ greater than 0.5, $PNFI = 0.750$ greater than 0.5, indicating that the model is simpler and obtain a better fitting goodness. The incremental fit measures $IFI = 0.986$ greater than 0.9, $CFI = 0.986$ greater than 0.9 and the absolute fit measures $GFI = 0.901$ greater than 0.9, $RMSEA = 0.023 < 0.05$. To sum up, the relationship between the user psychological constructs and the significant measures of psychological constructs are well fitted by the SEM analysis.

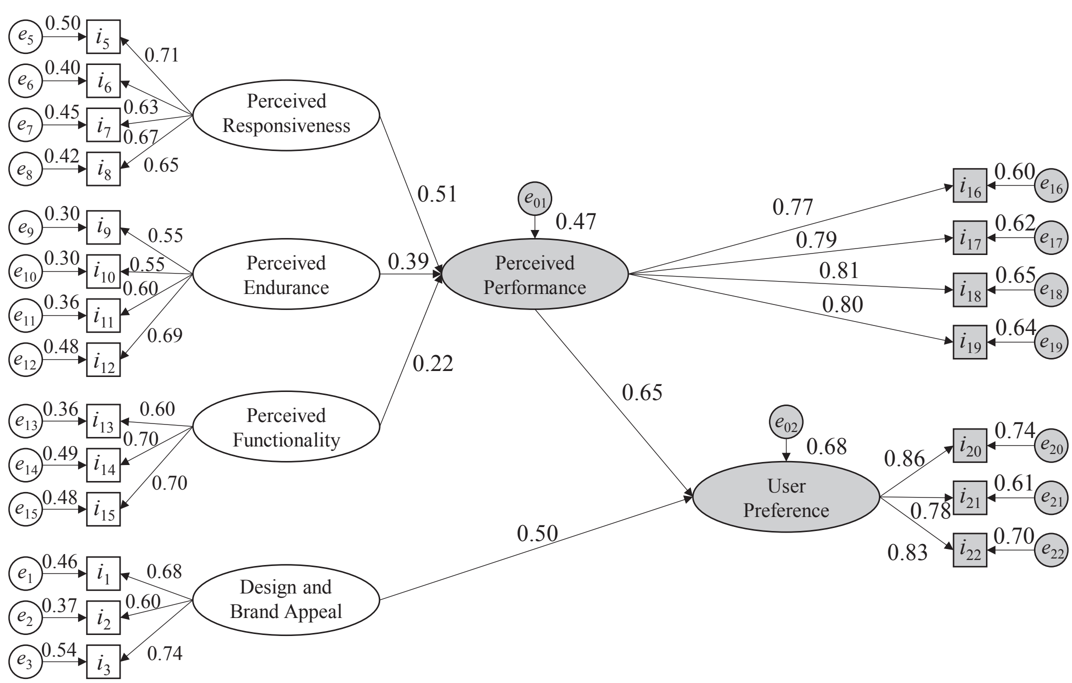

Fig. 5. The fitting results of user perception model based on SEM.

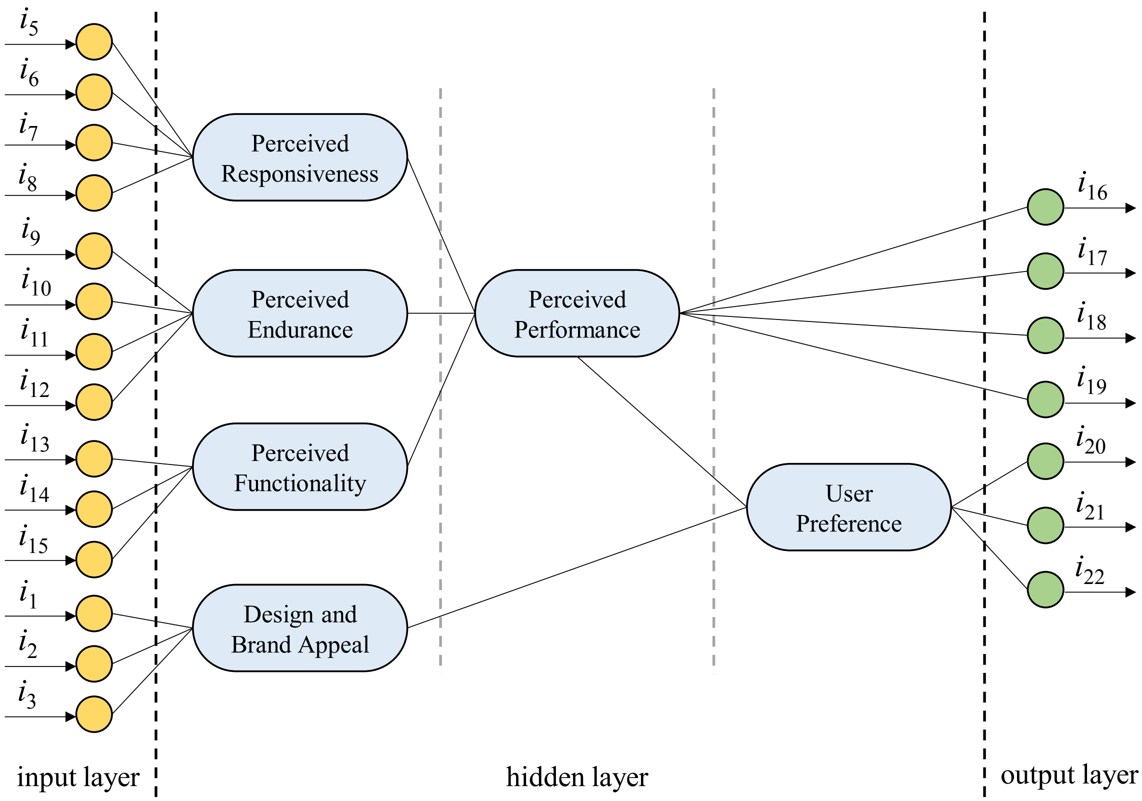

Fig. 6. The SEM-based ANN for smartphone consumer preference analysis.

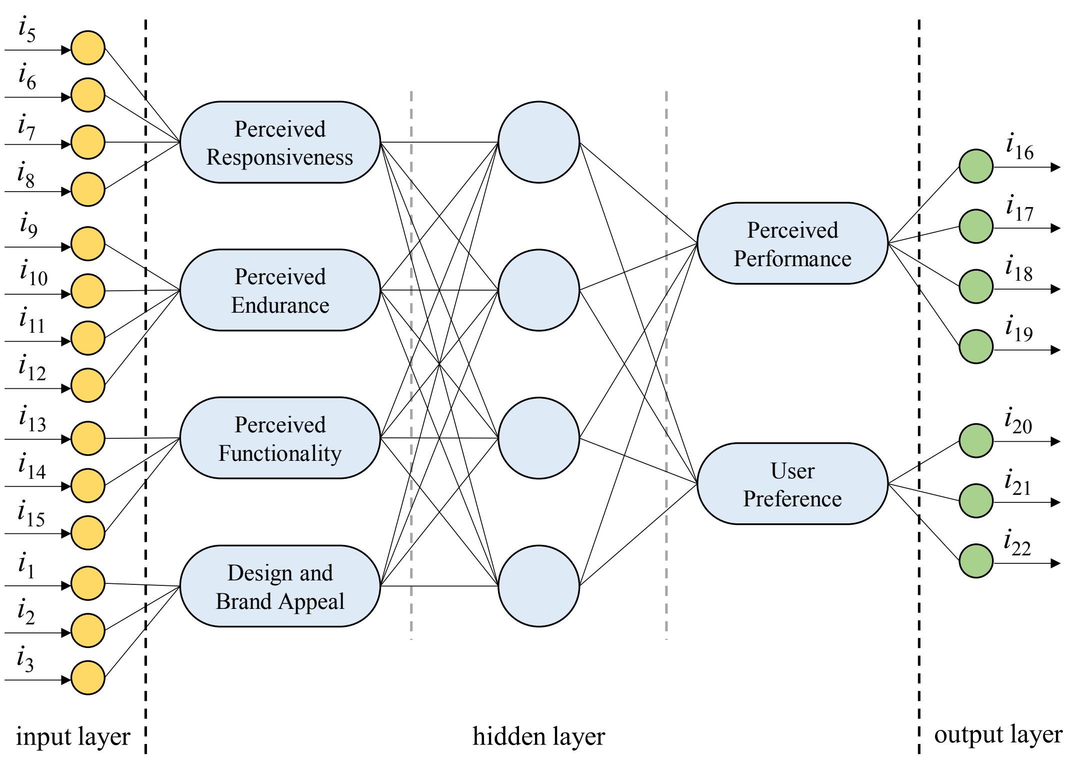

Fig. 7. An example of a fully connected neural network for this problem.

3.3. Phase II: Path coefficient revision

The topological structure of the SEM is established, as shown in Fig. 6. This SEM-based ANN can be regarded as an ANN model with partially connected nodes, and the number of hidden layers and the number of nodes in each layer are known. This neural network model should outperform a typical fully connected network (as shown in Fig. 7) in terms of training speed and prediction performance, as it has

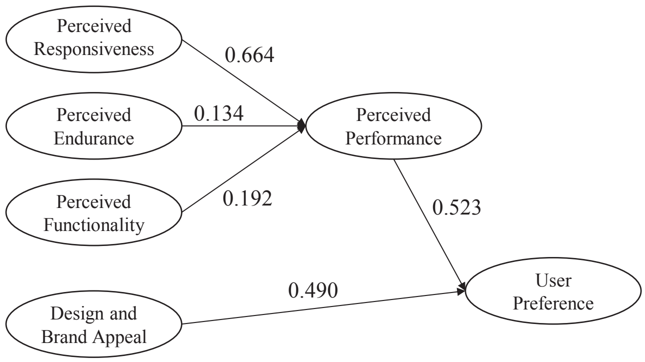

Fig. 8. The revised path coefficients.

Table 5
The evaluation results of ANN.

Item	Perceived Performance				User Preference		
Measures	i_{16}	i_{17}	i_{18}	i_{19}	i_{20}	i_{21}	i_{22}
RMSE	0.07	0.11	0.07	0.05	0.06	0.17	0.04
R^2	0.65	0.72	0.72	0.70	0.79	0.66	0.77

Table 6
Fit indices of ANN.

Fit Indices	χ^2	χ^2/df	PGFI	PNFI	IFI	CFI	GFI	RMSEA
Value	215.384	1.055	0.731	0.818	0.962	0.982	0.945	0.012

fewer nodes and fewer connections.

A program of BP neural network is written in Python. The 5-fold cross-validation is used to calculate the average prediction accuracy. The data are organized into five 80%-20% training/test splits, i.e., using 134 samples as training data and the remaining 34 samples as test data each time. After standardizing the input and output data, the model training is carried out. The training rate is set to be 0.1, and the training times are set to be 2000. When the training time is reached, the network training is ended. The test data then be used to evaluate the quality of the trained model. The revised path coefficients (i.e. connection weights) are shown in Fig. 8 and the index of *RMSE* and R^2 of the model are calculated as shown in Table 5. The *RMSE* of all those reflective measures of the test data are around 0.1, even though the maximum error is also less than 0.2, which indicates that after iterative training by 2000 times, the model has converged. The R^2 of each reflective measure is more than 0.5, indicating that the model is well fitted. The fit indices of the ANN are shown in Table 6.

3.4. Discussion

3.4.1. Discussion on the Goodness-of-fit

The goodness of fit of the proposed SEM-NN model is compared with that of the conventional SEM and the nonlinear SEM. Here, the nonlinear structural equation mixture models (NSEMM) in Ref. [26] is selected as the nonlinear SEM. In NSEMM, finite mixtures of linear SEMs are used to approximate the unknown nonlinear relationship of the latent variables. Considering the specifics of our case study, the NSEMM approach is used in *indirect applications* to approximate the non-normal distributions of latent variables In other words, The mixtures are not given a substantive meaning and mixtures are only used to approximate nonlinearity and nonnormality [48]. Table 7 reports the R^2 of those reflective measures (from i_{16} to i_{22}) of the three SEM techniques. The results suggest that the fitting goodness of the NSEMM is better than that of conventional SEM, and the fitting goodness of the proposed SEM-NN model is even better than that of NSEMM. Thus, the fitting goodness of the model are improved by combining the SEM and the ANN. The SEM-NN model can model the nonlinear relationship between variables better than conventional SEM approach.

Table 7
The R^2 of three SEM techniques.

Model	Perceived Performance				User Preference		
Measures	i_{16}	i_{17}	i_{18}	i_{19}	i_{20}	i_{21}	i_{22}
Conventional SEM	0.60	0.62	0.65	0.65	0.74	0.61	0.70
NSEMM	0.62	0.67	0.70	0.65	0.76	0.62	0.73
SEM-NN	0.65	0.72	0.72	0.70	0.79	0.66	0.77

Table 8
The normalized path coefficients of SEM and SEM-NN.

Influence Path	SEM	SEM-NN
Perceived Responsiveness → Perceived performances	0.456	0.664
Perceived Battery Endurance → Perceived performances	0.346	0.134
Perceived Functionality → Perceived performances	0.198	0.192
Perceived performances → User Preference	0.565	0.523
Design and Brand Appeal → User Preference	0.435	0.490

3.4.2. Discussion on the casual relationship

The path coefficients for the conventional SEM and the trained connection weights between the neurons in hidden layer for the ANN are shown in Table 8. The results of the conventional SEM show that the ranking orders of the dimensions that can most affect user's perceived performance are the perceived responsiveness, the perceived battery endurance and the perceived functionality, while the ranking result of SEM-NN is the perceived responsiveness, the perceived functionality and the perceived endurance. Besides, the value differences indicate that the perceived responsiveness is much more important than the other two dimensions. The results of SEM-NN are more in line with the current development trend of the current smartphone market, that is, the improvement of the smartphone's responsiveness and functionality has been the fundamental strategy for manufacturers to improve product differentiation. The battery endurance is less important than the above two dimensions. For example, the manufactures are all developing and optimize their own Operating System (OS), such as the EMUI OS of Huawei and the MIUI OS of Xiaomi. Besides, Huawei is cooperating with Leica to launch a smartphone with dual cameras, and the Apple recently released a smartphone with the function of face recognition. All these strategies are focus on the enhancement of the perceived responsiveness and functionality and then provide better experiences for smartphone users.

Table 9 shows the relative weights of measurement items of each user perception in two models. The results show that the relative weights of measures of some user perceptions are basically the same in two models, while the others are quite different. For example, for the Perceived Responsiveness, the relative weights of those four measures (i_5, i_6, i_7, and i_8) in the conventional SEM are almost same, while the relative weight of i_7 in the SEM-NN is significantly lower than i_5, i_6 and i_8. In the questionnaire, i_5, i_6, i_7, and i_8 correspond to the performance of ROM, RAM, mobile connectivity, and CPU, respectively. The results of SEM-NN show that compared with the other three measures, the performance of mobile connectivity of a smartphone has a relatively small influence on the Perceived Responsiveness, which is consistent with the actual situation. By introducing the BP algorithm to the training of the conventional SEM, not only the influence path of the model is reserved and improved, the shortage of the SEM method like the linearity is also overcome by using the nonlinear fitting ability of the BP algorithm. The comparison shows that the analysis results of SEM-NN could be more in line with the actual situation.

Table 9
The relative weight of measurement items in SEM and SEM-NN.

User Perception	Measurement Items	SEM	SEM-NN
Design and Brand Appeal	i_1	0.337	0.128
	i_2	0.299	0.345
	i_3	0.364	0.527
Perceived Responsiveness	i_5	0.266	0.260
	i_6	0.237	0.319
	i_7	0.252	0.123
	i_8	0.245	0.298
Perceived Battery Endurance	i_9	0.231	0.431
	i_{10}	0.230	0.177
	i_{11}	0.250	0.070
	i_{12}	0.289	0.322
Perceived Functionality	i_{13}	0.301	0.104
	i_{14}	0.350	0.742
	i_{15}	0.349	0.154
Perceived Performance	i_{16}	0.243	0.236
	i_{17}	0.249	0.194
	i_{18}	0.255	0.315
	i_{19}	0.253	0.255
User Preference	i_{20}	0.348	0.358
	i_{21}	0.315	0.336
	i_{22}	0.337	0.306

According to the Kano model [49], customer needs can be divided into the basic needs, the expected needs and the unexpected needs. The basic needs are the function or service that the product must provide. For smartphone, more and more files and applications need to be installed and users often open multi applications at the same time. Hence, the performance of ROM, RAM and CPU can be the basic needs for that these functions seriously affect a user's perceived performances. The improvement of these performances will gradually increase the user satisfaction. When these performances are improved to a certain extent, the increase of the customer satisfaction will face a marginal diminishing effect. That means the relationship between the performance improvement and the satisfaction increases are nonlinear, which is difficult for the conventional SEM to interpreter.

4. Conclusions and future work

In the design process of consumer products, a primary task is establishing a mapping relationship between consumer preferences and product attributes. The proposed SEM-NN approach can be useful to help the designers to identify and map how product attributes affecting the fulfillment of user perceptions and ultimately their preferences, and to better understand the factors that affect user perceptions and the inner relationships between them. The SEM-NN model can make full use of the causal analysis of SEM and the nonlinear nature of ANN and overcome their drawbacks to some extent. The main contributions of the article are as follows:

(1) A SEM-NN model for consumer preference analysis is introduced for identifying and mapping how product attributes affecting the fulfillment of user perceptions and ultimately their preferences. In this model, the consumer preference analysis is conducted in two phases: influence path construction, and path coefficient revision.
(2) To solve the problem that some of the relationships between variables are nonlinear in nature, the BP algorithm is conducted after the conventional SEM to obtain the revised path coefficients. The SEM-NN model can make full use of the causal analysis of SEM and the nonlinear nature of ANN and overcome their drawbacks to some extent.
(3) The topological structure of the ANN is obtained from the conventional SEM model. Employing the results from SEM provides a way to develop a neural network model with a good prediction performance. In general, the topology of an ANN is a fully connected network, and the meaning of neurons in the hidden layers are unknow. In addition, it is often difficult to construct a neural network model when learning from data.

A smartphone case study is used to demonstrate the effectiveness of the proposed approach. Using the case study, we demonstrated how SEM and ANN can be used together to describe the nonlinear relationship between potential variables more accurately. We also demonstrate that employing the results from SEM provides a way to develop a neural network model with a better prediction performance than a fully connected network. In practice, with the increasing complexity of the measurement model and the structural model, there is a possibility that the relationships among the psychological constructs are nonlinear in nature. The proposed two-phased SEM-NN approach can be useful to reveal such relationships more accurately and more efficiently. In addition to consumer preference analysis, this approach can also be used in other fields where SEM techniques are frequently applied, such as product design and improvement, psychology, sociology, management, product design, etc.

While the insights and results are encouraging, there remains potential for further studies and advances. Currently, the measurement items are all evaluated through questionnaires. In the future research, with the popularity of the Internet of Things and the wide application of embedded sensors in products, the interactive data between user and product can be collected and used to make the model more accurate and objective.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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